Space, Time, and Temperature in Streams: Towards a General Framework for Understanding and Prediction of Thermal Regimes

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What is a Regime?

Temporal variation characteristic to a site

Maheu et al. 2015. A classification of stream water temperature regimes. *River Research & Applications*
Factors Causing Temporal Variation

Environmental covariates

Sun angle

Riparian changes

Climate forcings

Air Temp (°C) vs. Discharge (m³/s)

Factors Causing Temporal Variation

Heat budget mechanisms

- Shortwave radiation
- Sensible heat
- Longwave radiation
- Bed friction
- Advection

Factors
Causing Temporal Variation
Heat budget mechanisms

Regimes Vary in Space
Covariates & heat budgets differ in different places
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~300,000 stream kilometers
Regimes Vary in Space
Covariates & heat budgets differ in different places
~300,000 stream kilometers

Maheu et al. 2015.
Space-Time ANOVA Variance Decomposition

\[ \text{Var}_{\text{total}} = \text{Var}_{\text{space}} + \text{Var}_{\text{time}} + \text{Var}_{S*T} + \text{error} \]
An Example with Real Data

~4,000 annual monitoring sites in PNW
Central Idaho Temperature Network

167 Sites
Since 2010
Space-Time Variance Decomposition

Summer Mean Stream Temperature

Mean August Temperature (°C)

Elevation (m)

$r^2 = 34\%$

Var_{Space} = 7°C

Spatial gradient
Space-Time Variance Decomposition

Summer Mean Stream Temperature

- Air Δ = +3.0°C
- Discharge Δ = -28%
- Var_{Time} = 1.30°C

Regression Statistics

- Multiple R = 0.602218
- R Square = 0.362666
- Adjusted R Square = 0.356872
- Standard Error = 2.349002
- Observations = 334

ANOVA

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<tr>
<th>df</th>
<th>SS</th>
<th>MS</th>
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<tr>
<td>Total</td>
<td>333</td>
<td>2857.025</td>
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Coefficients

- Intercept: 17.18042, t Stat = 30.59785, P-value = 2.23E-98
- ELEV(S): -0.00391, t Stat = -9.12702, P-value = 7.17E-18
- Year(T): 1.201441, t Stat = 1.510036, P-value = 0.131991
- S&T: -1.6E-05, t Stat = -0.02606, P-value = 0.979227

Spatial gradient
Space-Time Variance Decomposition

Summer Mean Stream Temperature

$\text{Var}_{S*T}$

Temperature (°C)

Elevation (m)

2013

2010
Space-Time Variance Decomposition

Summer Mean Stream Temperature

Average change across sites =

\[ \text{Var}_{\text{Time}} = 1.30^\circ \text{C} \]

\[ \text{Var}_{S \times T} = 0.37^\circ \text{C} \]

Site level deviation from average change
Space-Time ANOVA Variance Decomposition

$$\text{Var}_{\text{total}} = \text{Var}_{\text{space}} + \text{Var}_{\text{time}} + \text{Var}_{S*T} + \text{error}$$

- \( \text{Var}_{\text{space}} = 7^\circ C (84\%) \)
- \( \text{Var}_{\text{time}} = 0.93^\circ C (11\%) \)
- \( \text{Var}_{S*T} = 0.37^\circ C (5\%) \)
- \( \text{Var}_{\text{error}} \)

\( \text{Var}_{\text{total}} = 8.3^\circ C \)
Different **Extent** & **Grain** = Different **Variance Structure** *(spatial dimension)*

Big network = great spatial heterogeneity

Small network = little spatial heterogeneity

Kotlier and Wiens 1990
Same Extent & Different **Grain** =  
Different Variance Structure

Big network = sparsely sampled

Kotlier and Wiens 1990
Different Extent & Grain = Different Variance Structure (temporal dimension)

Long duration (100 years) = much variation

Webb and Nobilus 2007

Short duration (1 week) = limited variation

Kotlier and Wiens 1990
Different Extent & Grain = Different Variance Structure

Short duration, densely sampled

Hourly measurements...

5/21/2012

Temp (°C)

25
20
15
10
5

Short duration, sparsely sampled

Daily measurements...

5/21/2012

Temp (°C)
How We Model Also Affects Interpretation of Variance Structure

\[ \text{Var}_{\text{time}} = 100\% \]

\[ \text{Var}_{\text{space}} = 100\% \]
Many Accurate Predictive Tools...

But Prediction ≠ Understanding

Regression trees

Neural networks

Wavelets

I'm old fashioned, I'd really like to have a parameter estimate that links temperatures to some heat budget component or covariate.
Understanding = Attribution of Variance

“Why” do temps change through space & time?

Mechanistic

Correlative
An Attempt at Best of Both Worlds: Understanding and Prediction

Why we've gravitated towards using new SSN geostats for networks...

800,000 stream kilometers & counting...
Accurate Prediction & Attribution of Variance to Covariates

- Covariate Predictors
  1. Elevation (m)
  2. Canopy (%)
  3. Stream slope (%)
  4. Ave Precipitation (mm)
  5. Latitude (km)
  6. Lakes upstream (%)  
  7. Baseflow Index
  8. Watershed size (km²)
  9. Glacier (%)
  10. Discharge (m³/s)
  11. Air Temperature (°C)

- n = 48,000 summers of data
- 21 years (1993-2013)
- $R^2 = 0.90$
- RMRS = 1.0°C
Measuring Covariates & Heat Budgets are Big Challenges

Correlative models = crude covariates limit understanding

Mechanistic models = intensive measurements limit extent

Proportion of total variation

Error

Var(S*T)

Var(Time)

Var(Space-autocorr)

Var(Space-covariates)
Measuring Covariates & Heat Budgets are Big Opportunities

High resolution air temperature models

Satellite & drone sensors

Bigger/faster computers & GIS

Hybrid model approaches?
Data are not limiting
(>5,800 annual monitoring sites & growing)

~50,000,000 hourly records/annually!

>50,000,000 hourly records
>18,000 unique stream sites
Challenges are Not Limiting

Need for better prediction & understanding will intensify

- **Climate Change**
- **Urbanization & Population Growth**
- **Shrinking Budgets**
  - Need to do more with less